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Topological Considerations on Decentralised Energy Exchange in the Smart Grid

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Abstract

The realisation of the Smart Grid envisions end-users, equipped with renewable energy generators such as solar panels, to act as “prosumer”. The prosumer is engaged in both energy production and consumption, and its energy can be exchanged as a commodity between end-users, disrupting the traditional power system distribution model. To facilitate the transition to a prosumers’ governed grid, we proposed a novel strategy for optimising decentralised energy exchange in the Smart Grid and tested it on a radial test feeder. In this paper, we consider the topological effects on the distribution of evaluating various topologies of the test feeder based on the optimisation strategy proposed in our previous work. We simulate the energy exchange based on the Monte Carlo method and compare the performance of different topological shapes. Overall, the complete graph has better performance than other topological shapes. But it is not a practical topology because of its high implementation costs. For other topologies, the random graph has higher efficiency than others in reducing the maximum load in electric lines and hopping count of energy delivery, and the small-world is relative more efficient in decreasing energy loss of delivery and energy costs for end-users.

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Keywords: topology; energy distribution; Smart Grid; Monte Carlo simulation

1. Introduction

The Smart Grid is an evolution of the Power Grid that adopts Information and Communication Technology (ICT) to enhance its efficiency, reliability, and environmental sustainability.² Traditional power systems are centralised with energy generation at the top of a hierarchical structure (e.g., large thermal power generation). However, the Smart Grid visions distributed energy generators (i.e., solar panels and small wind turbines) based on renewable energy sources and decentralised energy exchange in distribution networks envisioning following bidirectional energy flows. The end-user, which can be equipped with a distributed energy generator and engaged in both energy production and consumption, is called a *prosumer*. After fulfilling the individual needs of the prosumer, its surplus energy can be stored or sold.

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Trading of surplus energy among prosumers in the distribution network is decentralised energy exchange. By contrast, centralised energy distribution means that end-users buy energy from or send their surplus energy to a controlling centralised operator. The prosumers, and decentralised and centralised energy exchange compose a Prosumer-involved Smart Grid.

In our previous work,¹⁶ we focused on optimising decentralised energy exchange in the Prosumer-involved Smart Grid. The major optimisation objectives are to decrease energy loss of delivery, and to reduce energy cost for end-users. To achieve these goals, we proposed a model of the optimisation problems and the solution. We evaluated the solution by a test feeder with the radial topology. The results show that compared to the traditional power system, the maximum reduction of energy loss and energy costs based on our solution can achieve 51% and 66%, respectively.

In the present work, we study the effects of varying topologies by evaluating them on the test feeder by the Monte Carlo method.¹⁰ From a topological point of view, we compare the performance of different topology models based on the optimisation solution proposed in our paper.¹⁶ Overall, the complete graph has better performance than other topologies. But it is not practical because of its high implementation costs. The random graph has higher efficiency than others in reducing the maximum load in electric lines and hopping count of energy delivery, and the small-world is relative more efficient in reducing energy loss of delivery and costs of buying energy for end-users.

The major contributions of this paper are: (i) a proposal for evaluating how the topologies influence the performance of decentralised energy exchange, (ii) an experiment from a topological point of view based on the decentralised energy exchange, and (iii) a simulation model based on the Monte Carlo method and various statistical distributions.

The remainder of this paper is organised as follows. Section 2 illustrates the proposed approach. Section 3 presents the optimisation of decentralised energy exchange. In Section 4, the simulation methods are described. Assessment metrics are presented in Section 5. The results are discussed in Section 6. Section 7 concludes the paper.

2. Approach and Method

To evaluate the different topologies, we resort to the Monte Carlo method, which is a stochastic simulation relying on repeated random number generation and statistical analysis.^{10 15} Because the Monte Carlo method is closely related to random experiments that the specific results are not known in advance.^{10 15} In this method, we employ various statistical distributions to generate the renewable energy production, the energy consumption of end-users, and real-time energy price. Then the simulation of decentralised energy exchange repeats multiple times to produce statistically relevant results. The procedure of the Monte Carlo method starts with setting the number of simulation repeat times. Then, it generates random numbers as input parameters. For each set of input parameters, we run the simulation and get a set of output values. Each output value is one particular outcome scenario in the simulation run. Finally, the simulation is repeated until the setting of repeat times is fulfilled.

In Pagani and Aiello,¹³ we showed that the small-world¹⁸ model has a good balance between cost of upgrading the infrastructure and efficiency of distribution. Therefore we select the small-world model to generate the core of the distribution network. Compared to the other topology models, the small-world model with the average node degree $\langle k \rangle = 4$ and a rewiring probability $p = 0.4$ captures the requirements for the performance of local energy exchange and the costs of realisation.^{12 13 14}

The small-world model is a connection topology lying between completely regular graph or completely random graph. Therefore we select the random graph model with the same rewiring probability $p = 0.4$ for comparison. A random graph is obtained by beginning with a set of isolated nodes and adding successive edges between them at random.¹¹ For the regular graphs, we select the radial model and the complete graph model for comparison.

3. Decentralised Energy Exchange Optimisation

By decentralised energy exchange, we mean an energy distribution model in which any party connected to the network can trade and deliver energy to anyone else. In this section, we briefly describe this model and its optimisation problem definition, while for further details, we refer to our paper.¹⁶

Prosumers produce energy and consume it directly. They also can sell their surplus energy at real-time prices to anybody on the network, if their energy production exceeds their energy consumption. In the opposite case, prosumers become consumers buying energy from other prosumers or the electric utility. The end-users without the generators are simply consumers. The distribution network delivers energy among end-users with possible energy losses and under

the governing physical constraints. This model is based on the following major assumptions: (i) Buying and selling energy are considered by the system as random discrete events. (ii) Buying and selling energy are independent. (iii) All events at any two different time slots are independent. (iv) At one time slot, a prosumer can be either a consumer or a provider. (v) There is energy loss in electric lines when delivering electrical energy and the relevant costs are paid by consumers. (vi) Energy loss in substations and transformers is not considered. (vii) We only consider the active power.

In the proposed model, energy can have different routes depending on pairwise agreements and overall energy balance. Thus, energy losses can vary per transaction. For saving the costs of buying energy, consumers decide from which providers to buy energy and which delivery paths are used to deliver energy. In this scenario, the optimisation problems proposed in our paper¹⁶ is concerned with “how to search the cheapest energy providers considering energy prices and energy loss, and how to organise delivery paths with minimum energy loss”.

As a point of notation, we consider a system with $EU = \{eu_1, eu_2, \dots, eu_N\}$ end-users of cardinality N . The set of time slots is represented by $\Delta T = \{\Delta t_1, \Delta t_2, \dots\}$ and $\Delta t_i = \Delta t_j$ ($i \neq j$) and common to all users. A set of energy consumers at Δt is defined as $EC(t) = \{ec_1, ec_2, \dots, ec_n\}$. A set of energy providers at Δt is defined as $EP(t) = \{ep_1, ep_2, \dots, ep_m\}$, where $n + m \leq N$. For each provider, we have $ep_i = (p_i, v_i)$, in which p_i denotes the energy price (€/kWh) of ep_i and v_i denotes the amount of energy provided by ep_i . The energy amount that ec_i buys from ep_j is denoted by $b_{i,j} \in (0, v_j]$. The energy produced and consumed by eu_i are denoted by G_i and C_i , respectively. Thus, we have $Q_i = G_i - C_i$ denoting the amount of energy that eu_i can sell or needs to buy. If $Q_i > 0$, there is surplus energy for eu_i to sell. If $Q_i < 0$, eu_i needs to buy energy to meet its demand. If $Q_i = 0$, eu_i is self-satisfied.

For the consumer ec_i , the cost of buying an amount of energy x is denoted by $CoB(x)$. Energy loss of delivering x to the consumer is denoted by $LoD(x)$. The delivery path from ep_j to ec_i , consisting of electric lines without substations or transformers, is $PATH(j, i) = \{e_1, e_2, \dots\}$. Energy loss in $e \in PATH(j, i)$ is denoted by L_e . Thus, when $Q_i < 0$, the objective function of optimising energy cost for ec_i at any given time slot is the following:

$$\begin{cases} CoB(|Q_i|) = \min \sum_{j=1}^{|EP(t)|} (p_j \times (b_{i,j} + LoD(b_{i,j}))) \\ LoD(b_{i,j}) = \min \sum_{\forall PATH(j,i)} \left(\sum_{e \in PATH(j,i)} L_e \right) \end{cases} \quad (1)$$

We assume that a prosumer can only be a consumer or a provider at the same time slot and the set of prosumers is a subset of the set of end-users. Then, we have two constraints on end-users that are the followings:

$$EC(t) \cap EP(t) = \emptyset; \quad EC(t) \cup EP(t) \subseteq EU$$

The total amount of energy consumption and the total supply at each time slot has to be in balance. Generally, outputs of renewable energy generators depend on weather conditions which are not stable. To solve this problem, the model introduces a super agent (i.e., electric utility) to sell or buy energy at fixed prices when the total outputs of prosumers and the total consumption needs are unbalanced. The amount of energy to be balanced by the super agent at Δt is $ES(t)$. If $ES(t) > 0$, the super agent sells energy to the consumers. If $ES(t) < 0$, it buys the surplus energy from the providers. If $ES(t) = 0$, there is no energy trading on the super agent. Then, we have following constraints:

$$|Q_i| = \sum_{j=1}^{|EP(t)|} b_{i,j}; \quad \sum_{i=1}^{|EC(t)|} |Q_i| = \sum_{j=1}^{|EP(t)|} v_j + ES(t); \quad \sum_{i=1}^{|EC(t)|} C_i = \sum_{j=1}^{|EP(t)|} G_j + ES(t)$$

The model also considers two physical constraints of the distribution network. They are ampacity, the maximum current-carrying capacity of an electric line,⁶ and the direction of the energy flow (i.e., electric current) in the electric line. The ampacity of the electric line e_k is denoted by $I_{e_k}^{max}$, and the energy capacity of electric line is $I_{e_k}^{max} \times V_{e_k} \times \Delta t$ where V_{e_k} is the voltage of electric line. The energy flow that starts from ep_j going through e_k is denoted by $f_{(e_k, ep_j)}$, and the direction of $f_{(e_k, ep_j)}$ is denoted by $d_{(e_k, ep_j)} = \{-1, 1\}$. Then, we have following constraints:

$$\sum_{ep_j \in EP(t)} f_{(e_k, ep_j)} \leq I_{e_k}^{max} \times V_{e_k} \times \Delta t; \quad \sum_{ep_j \in EP(t)} d_{(e_k, ep_j)} = |d_{(e_k, ep_j)}|;$$

4. Simulation Setup

To evaluate the topologies proposed in Section 2, we build a simulation program in Java to represent the Prosumer-involved Smart Grid. This simulation program models end-users, prosumers, real-time pricing, energy production, energy consumption, energy loss of delivery and a distribution network based on an IEEE test feeder.

4.1. Distribution Test Feeder

For the simulation we use the standard IEEE Distribution Test Feeder consisting of 37 nodes and three phases as the radial topology.⁹ We apply the following modifications to adapt this test feeder for our simulation. Since our simulation does not model the transformer and regulator, we remove these elements from the test feeder. We use the desired voltage on a 120 volt base as the voltage for all lines in the test feeder. We focus on the active power and assume that all of the nodes in this test feeder are end-users. Another assumption is that distributed loads of different phases are balanced. The topology of this modified test feeder is shown in Figure 1(a). We use GraphStream¹ to generate the topologies for the small-world model and random graph with 37 nodes. The sample graphs of the small-world model and random graph are indicated in Figure 1(b) and Figure 1(c), respectively. We assume that all the lines in all topologies are with same length and material. Meaning that all lines have same electrical properties.

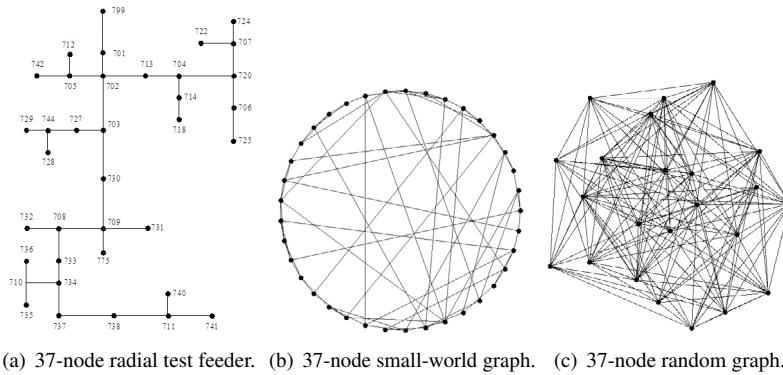


Fig. 1: IEEE test feeder and topologies.

4.2. Wind energy production

We apply two types of renewable energy generators, small wind turbines and solar panels. For a prosumer, we randomly choose one of them for energy production at the beginning of the simulation. A prosumer is modelled only having one wind turbine.

Wind power flowing through a wind turbine depends on the length of its rotor blades, air density and wind speed. The formulas of producing electric power P_w and electrical energy E_w by a wind turbine are derived from Grogg's paper.⁷ and are shown in Equation (2).

$$\begin{cases} P = 0.5 \times A \times \rho \times v^3 \times C_w \\ P_w = \min(P, P_{max}) \\ E_w = P_w \times \Delta t \end{cases} \quad (2)$$

The unit of P_w is Watt and the unit of E_w is Joule. The area swept by the blades (m^2), air density (kg/m^3) and wind speed (m/s) are denoted by A , ρ and v respectively. We use $C_w \in (0, 1)$ to denote the efficiency of a wind turbine. A wind turbine has maximum power output P_{max} (Watt).

¹ <http://graphstream-project.org>

In the simulation, we use the data of the standard three-bladed turbine introduced in the paper of Bukala *et al.*⁴ where $A = 10.75$ and $P_{max} = 2600$. For C_w , we apply the efficiency curve of this turbine as is presented in the same paper.⁴ For air density, we use $\rho = 1.225$ that is the typical value of air density.

We apply a Weibull probability distribution to generate the wind speed. Parameters of shape and scale for the Weibull probability distribution are from Ayr's paper.³ We choose the data of Milano Malpensa where the shape is 1.4 and the scale is 3.18, due to its inland location. Meaning that the wind speed of this area is not influenced by oceans or mountains.

4.3. Solar energy production

The formulas of producing solar power P_s and electrical energy E_s by a solar panel are shown in Equation (3)². To model a realistic situation, the number of solar panels installed for a prosumer is randomly selected in 2, 4, 6, 8. Then, we sum the production of each solar panel to obtain the total energy production of the whole installation.

$$\begin{cases} P = A \times r \times C_p \times Q \\ P_s = \min(P, P_{peak}) \\ E_s = P_s \times \Delta t \end{cases} \quad (3)$$

The unit of P_s is Watt and the unit of E_s is Joule. The surface area of a solar panel (m^2) and solar radiation (W/m^2) are denoted by A and r , respectively. We use $C_p \in (0, 1)$ to denote the efficiency of a solar panel. We use $Q \in [0.5, 0.9]$ to denote the Quality Factor (Performance Ratio) that includes all loss relating to the solar power production of the solar panel. The peak power output of the solar panel is P_{peak} (Watt).

In the simulation, the solar panel that we choose is LG360Q1C³ where $C_p = 0.196$, $A = 1.73$ and $P_{peak} = 360$. For the Quality Factor, we use $Q = 0.75$.

The hourly solar radiation is calculated according to the simple sky model as proposed in the paper of Sung *et al.*¹⁷ and the Algorithm 3 in Grena's paper.⁵ The calculation takes into account clearness index, geographical location, local time, pressure, and temperature. The hourly clearness index is drawn by a normal probability distribution with mean value in $[0.4476, 0.64811]$ and standard deviation of 0.14 that are proposed in the paper of Jurado *et al.*⁸

4.4. Energy consumption and price

We assume that the hourly electrical energy consumption of end-users can be drawn by a bimodal probability distribution. Because it is a continuous distribution that has two peaks. These two peaks can be applied to modelling the two peaks of energy consumption in a day. Generally, the bimodal probability distribution can be considered as two individual normal probability distributions that are superimposed. We assume that the boundary of two peaks is 11 : 00 AM meaning that there is a energy consumption peak in the morning and there is another one in the afternoon. We calculate the parameters of the bimodal probability distribution based on the dataset provided by Liander.¹ This dataset records the hourly electricity consumption of small customers (connection $\leq 3 \times 25$ amperes) in the Netherlands in 2009. Then, the mean and standard deviation of the energy consumption in the morning are 0.15 and 0.058, respectively. The mean and standard deviation of the consumption in the afternoon are 0.227 and 0.064, respectively.

We assume that the real-time price of energy is relevant to the energy demand. Meaning that the price changes hourly and increases when the total energy consumption of the distribution network increases. Therefore, the real-time price can be drawn by the bimodal probability distribution. It is composed of two normal probability distributions with the boundary at 11 : 00AM. We refer to the electricity price statistics in 2017 on the website "eurostat".⁴ We use the average energy price of "EU-28" (i.e., the European 28 countries) on this website, which is €0.2 per kWh, as the mean value of both normal probability distributions. We set 0.05 as the standard deviation of both normal probability distributions. We also set the minimum energy price to €0.05 per kWh. The energy price of the utility company is

² Photovoltaic Software: <http://photovoltaic-software.com/PV-solar-energy-calculation.php>

³ Product page (accessed on 30 December 2017): www.lgenergy.com.au/products/solar-panels/lg-neon-r-r/lg360q1c

⁴ http://ec.europa.eu/eurostat/statistics-explained/index.php/Electricity_price_statistics

fixed and should be higher than the mean value of the real-time price. Therefore, we choose the average energy price of “Euro area” on the same website, which is €0.22 per kWh, as the energy price of the utility company.

5. Evaluation

We consider two energy flow patterns. The first one is a *Radial-flow* that simulates the traditional energy distribution flow. Electrical energy goes from the electric utility (central provider) to all end-users in the test feeder. In this case, there are no prosumers. All end-users are consumers and all energy needs are supplied by the electric utility. The electric utility injects energy into the test feeder via Node 799 (Figure 1(a)). The energy is delivered to other end-users from this node. Node 799 is also an end-user, but the energy loss of delivering energy to this node is 0.

The second energy flow pattern is the *Optimal-flow*. It simulates the model and solution of the Prosumer-involved Smart Grid we proposed. Some of the end-users are prosumers; energy production and decentralised energy exchange are involved. The optimisation strategy of decentralised energy exchange in this case is based on our paper.¹⁶

The *Radial-flow* is only applied to the radial topology as energy flows in a traditional power system. The *Optimal-flow* is applied to all the four models of topologies. Therefore, there are total five evaluation cases that are “Central”, “Radial”, “Random Graph”, “Small-world”, and “Complete Graph”.

To verify the effectiveness of the proposed topologies, we design four assessment metrics. These are 1) energy loss in the distribution network to evaluate the efficiency of delivering energy, 2) energy costs for end-users to indicate the financial benefits of the topologies, 3) maximum load in electric lines to show how the topologies influence energy distribution flows, and 4) hopping count of delivering energy to evaluate the performance of transferring energy from one node to another. The measurement of all assessment metrics is based on the same load need satisfaction in all evaluation cases. For energy loss, the loss of delivering bought energy from prosumers and the electric utility are both counted. We use the radial topology with the *Radial-flow*, that is, evaluation case Central, as a *baseline* to assess the other four evaluation cases referred to as “Assessed Cases”, below.

To assess the influence of the number of prosumers, we have various prosumer settings for the evaluation cases of the *Optimal-flow*. Raising the number of the settings will slow down the simulation program. Moreover, a slight increase in the number of prosumers does not guarantee to clearly show the difference in the simulation results. Therefore, we only have two settings, $M = 18, 37$, for the number of prosumers. This means that 48%, 100% of the end-users are prosumers, respectively. These prosumer settings are referred to as “48%-prosumer” and “100%-prosumer”, respectively. For the radial topology with the *Radial-flow* (i.e., the baseline), the number of prosumers is always 0 that does not influence the simulation results.

In order to analyse simulation data, we run multiple instances of the simulation and calculate the mean values of all outputs for the metrics.¹⁰ We set the number of simulation runs per configuration to 2000. That is, we run the simulation for 2000 days and calculate the mean values for all outputs of these days for each evaluation metric. In these 2000 days, each day is randomly selected from four seasons in a year. In each iteration, each case runs once. Five evaluation cases share the same generated data of energy production, consumption, and prices. In each iteration, the number of time slot is $T = 24$ and $\Delta t = 1$ hour. To avoid conflicts that several consumers buy energy from one provider at the same time, the running of each end-user is isolated, independent and sequential. The sequence of running end-users is random at different each time slot. But in the same time slot, the sequences of running end-users for five evaluation cases are the same.

6. Discussion

One aim of our study is to evaluate energy loss of delivery in different topologies. The performance of average energy loss reduction is shown in Figure 2(a). Compared to the baseline Central, energy loss decreases in the Assessed Cases. The Complete Graph has better performance than other topologies in both settings of the number of prosumers. The Small-world is ranked second. Moreover, the efficiency of energy loss reduction in the test feeder improves with the rising number of prosumers from 48% to 100% of end-users.

Another aim of our study is to compare the performance of reducing energy cost for end-users in different topologies. The energy cost is the total amount of money paid by the end-user for buying energy over a day. The results in Figure 2(b) show droppings of average energy cost per end-user per hour in the Assessed Cases. Switching the setting from 48%-prosumers to 100%-prosumers, the efficiency of energy cost reduction has a significant enhancement.

However, the performance of different topologies in the same prosumer setting has slight differences. Thus, different topologies have no influence on this metric.

We design the maximum load metric in electric lines to show how topologies can influence energy loads of the test feeder during energy exchange. The performance of average maximum loads in one hour is shown in Figure 2(c). There are meaningful decreases in the Assessed Cases compared to the baseline. Random Graph and Complete Graph have the better performance. But there is a slight difference between the performance of the Random Graph and the Complete Graph. Furthermore, the settings of the number of prosumers does not have significant influence on this metric. The performances of 48%-prosumers and 100%-prosumers are very close.

The hopping count of delivery is to measure how many electric lines are needed to delivery energy from one provider to one consumer. The performance of the average hopping count metric for energy exchange is shown in Figure 2(d). Compared to the baseline, all Assessed Cases obtain meaningful reductions. The Random Graph has better performance than other topologies and the Complete Graph is ranked second. The difference of their performance is small. In addition, the settings of 48%-prosumers and 100%-prosumers have very close performance.

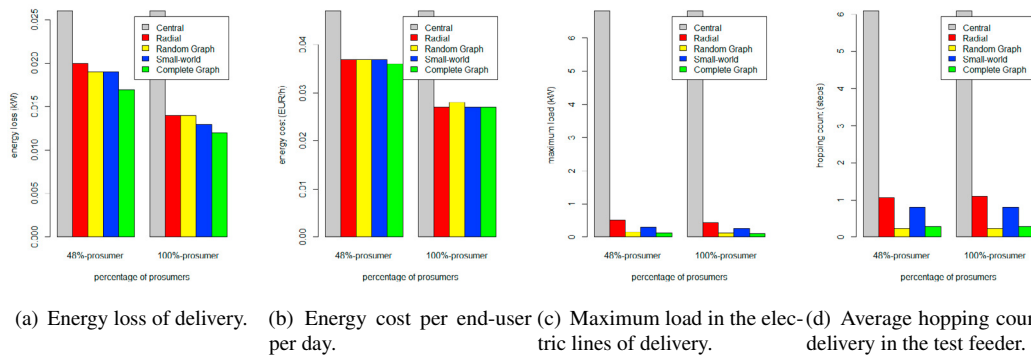


Fig. 2: Evaluation results of the metrics.

The figures give an indication of the overall performance of the Assessed Cases and how these significantly improve on the current baseline. To clearly indicate the improvement, we calculate the percentage of the reduction based on the baseline for all metrics and show the numerical data of the evaluation in Table 1. Compared to the baseline, the maximum reductions of energy loss, energy cost, and maximum load are 53.8%, 42.6%, and 98.3%, respectively. They are achieved by the Complete Graph with 100%-prosumers. The maximum reduction of hopping count is 96.3% achieved by the Random Graph with 48%-prosumers.

| Evaluation Cases | Central | Radial | Random Graph | Small-world | Complete Graph |
|--------------------|----------|------------------|------------------|------------------|------------------|
| Assessment Metrics | Baseline | 48/100%-prosumer | 48/100%-prosumer | 48/100%-prosumer | 48/100%-prosumer |
| Energy Loss | 0.026kW | -23.1/ - 46.2% | -26.9/ - 46.2% | -26.9/ - 50% | -34.6/ - 53.8% |
| Energy Cost | 0.047€/h | -21.3/ - 42.6% | -21.3/ - 40.4% | -21.3/ - 42.6% | -23.4/ - 42.6% |
| Hopping Count | 6.1 | -82.7/ - 82% | -96.3/ - 96.2% | -86.6/ - 86.7% | -95.2/ - 95.2% |
| Maximum Load | 6.806kW | -92.4/ - 93.6% | -97.7/ - 98.1% | -95.6/ - 96.4% | -98.1/ - 98.3% |

Table 1: Performance comparison with the evaluation cases.

Overall, the Complete Graph outperforms the other Assessed Cases. The reason of this outcome is linked to its full-meshed topology that provides an edge for each pair of nodes. But it is only an idealised case of topology that is rarely to be implemented in the realistic situation because of the high implementation costs. Considering more practical evaluation cases of topologies, the Random Graph and the Small-world both have their advantages in some metrics. The Random Graph stands out in maximum load in electric lines and hopping count of energy delivery that are independent of the setting of the number of prosumers. The Small-world is superior in other two metrics, energy loss in the distribution network and energy cost for end-users. The performance of these metrics are closely relevant to the number of prosumers.

7. Conclusions

We apply the Monte Carlo method to evaluating different topologies of the distribution network for decentralised energy exchange. We employ various statistical distributions to simulate renewable energy production, energy consumption of end-users and real-time pricing of energy. The model and solution of decentralised energy exchange optimisation come from our previous work.¹⁶ We propose five evaluation cases: “Central”, “Radial”, “Random Graph”, “Small-world”, and “Complete Graph”. We design four assessment metrics to compare the performance of evaluation cases. They are energy loss in the distribution network, energy cost for end-users, maximum load in electric line, and hopping count of energy delivery. Then, we run the simulation program of the evaluation and analyse the results. Overall, the Complete Graph has better performance than other topologies. But it is not a practical topology because it has high implementation costs. For realistic topologies, the Random Graph and the Small-world are practical and efficient. The Random Graph outperforms the Small-world in maximum load in electric lines and hopping count of energy delivery. The Small-world surpasses the Random Graph in decreasing energy loss in the distribution network and reducing the costs of buying energy for end-users.

According to the discussion in Section 6, the small-world topology is suitable for saving energy by reducing the energy loss of delivery. However, the random graph topology can decrease the construction costs of the distribution network. Because it does not need electric lines that have the high ampacity to carry heavy load. In the future work, it is our intention to introduce distributed energy storage systems (DESS, such as home batteries and electric vehicles) and add the optimisation of the charge/discharge cycle to the model. With DESS, prosumers are enabled to decide whether the excess energy should be sold for an immediate profit or stored for later use.

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